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CORRECTING RADIANCE DATA FOR RANDOMLY OCCURRING NONUNIFORM ILLUMINATION OF THE IFOV OF INDIVIDUAL DETECTORS IN ARRAYS

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ABSTRACT

This paper discusses the nonuniform illumination of individual pixels in an array that is intrinsic to the scene viewed, as opposed to turbulence or platform motion as an error source in quantitative imagery. It describes two classes of algorithms to treat this type of problem. It points out that this problem can be viewed as a type of inverse problem with a corresponding integral equation unlike those commonly treated in the literature. One class allows estimation of the spatial variation of radiance within pixels using the single digital number irradiances produced by the measurements of the detectors within their instantaneous-fields-of-view (IFOVs). Usually it is assumed without discussion that the intrapixel radiance distribution is constant. Results are presented showing the improvements obtained by the methods discussed.

Key words: detector array, nonuniform illumination, radiance spatial variation, inverse problem, quantitative imagery

I. INTRODUCTION

This paper discusses a source of error in quantitative imaging that has received little attention; the nonuniform illumination of individual detectors in arrays of detectors, and describes some techniques to reduce errors from this source. The nonuniform illumination is determined by that portion of a scene viewed at an instant by an individual detector that is not intrinsically random, however such nonuniformities of illumination are:

- unknown in advance
- vary in a way unknown in advance from detector to detector in the array since each detector usually views a separate portion of the scene, and
- vary in time in a manner unknown in advance (because of platform motion or time-varying scenes, or both).

Therefore such nonuniformities cannot be calibrated prior to the fielding of such sensors, and represent a potential source of errors that fluctuate with time from detector to detector. The errors arise from the fact that although the irradiance measured by each detector is produced by a spatially nonuniform radiance illuminating that detector's surface, the measurement process leads to a single digital number for each detector. This number represents an averaged value of radiance equivalent to some constant, often fictitious, spatial distribution of radiance across the detector surface.

The spatial nonuniformities of concern may reach significant proportions in circumstances such as when the image includes:

- small objects (comparable to the instantaneous-field-of-view (IFOV) of the detector)
- rapid or abrupt changes in properties of the surface viewed (such as at the edges of farm vegetation or buildings)
- fine topographic features of the ground, and rapid changes in surface altitude within the image.

Such nonuniformities are intrinsic to the scene viewed. There are other causes, extrinsic to what is to be imaged, but also of considerable importance and commonly occurring, such as atmospheric turbulence and platform motion. This paper will concentrate on the intrinsic problem and not make use of a physical model of an extrinsic blur mechanism, such as turbulence or platform motion. Contributing to the problem are aspects of the limited spatial resolution of all sensor systems.

This nonuniformity error source is one among many classes of error sources in optical imaging that are widely discussed and catalogued in the literature. See, e.g., [1]. Many of these error sources are from truly random processes, e.g., thermal and shot noise in detectors, but many are not, e.g., small unaccounted for optical system misalignments and atmospheric distortions. Nevertheless the general approach has been to try to estimate quantitative bounds on the errors these sources produce, and to develop techniques (e.g. atmospheric correction) that reduce their effects on the final product.

In this paper the terms IFOV and pixel often will be used interchangeably although they refer to different but intimately related aspects. What is viewed by the detector through its IFOV may be thought of as the input to an electro-optical system, while the pixel, in common circumstances, occurs in the system output. The usage here will be governed by common use, e.g. the expression "subpixel demixing" is commonly used but not "sub-IFOV demixing."

Errors in spatial imagery due to the nonuniform illumination of individual detectors appear to have been discussed only recently, see e.g. [2-5] and their references, and except for [2] and [5], do not seem to deal with effects intrinsic to the scene viewed. Nor does the error source, when intrinsic to the scene viewed, seem to be included in any of the past extensive error source catalogues. There are, however, some well known types of errors that should be mentioned. The first, pattern noise or pattern nonuniformity [6], arises from the unintentional differences between the recorded intensities of identically arrayed detectors due to manufacturing imperfections, and should not be confused with the error source discussed in this paper.

The second error source, though different than nonuniform illumination, may need to be considered in conjunction with some of the corrective methods discussed here if it is of significant magnitude in the detectors used in a specific application. This source of errors is usually determined by scanning a very narrow beam of illumination across the surface of a detector.

It is usually corrected by using the measured spatial variation to calculate an averaged intensity for the detector. If the measured spatial variation is small it may be sufficient. If not, the measured spatial variation for each detector, determined during calibration before fielding, must be retained and used as a weighting function in some of the corrective techniques being proposed here.

Two of the authors (Berger, Bosch) recently discussed a class of methods, called derivative-as-limit (DAL), to reduce the effect of nonuniform illumination of individual detectors on imagery accuracy [2]. This paper will discuss the nature of the fundamental problem to be dealt with, describe it as a type of inverse problem differing from those commonly found in the literature, and distinguish it from the related problems of subpixel spectral demixing and target location, and track it with subpixel accuracy. Then, it will discuss the DAL class of methods, propose another class to reduce imagery errors, and discuss and make use of a technique for determining centroids of what is viewed within individual pixels in an array.

II. THE NATURE OF THE PROBLEM

While it is the radiance that is usually desired, optical detectors measure irradiance. To determine radiance from that measurement, the fundamental relationship between the two quantities,

$$L = dE / d\Omega \qquad (1)$$

must be invoked. Here L = radiance, E = irradiance and Ω = projected solid angle. The integral form of this,

$$E_o = \int_{\Omega_o} L \, d\Omega \qquad (2)$$

also is useful. Here Ω_o is the projected solid angle subtended by the detector of interest and E_o is the irradiance measured by that detector.

Clearly if the illuminating radiance $L = f(\phi,\beta)$ is a known function of the angles ϕ and β, which locate a variable point on the surface of the individual detector, then integration over the surface of that detector yields a specific irradiance. Unfortunately it is $L(\phi,\beta)$ that is unknown and is the numerical value of the integral, E_o, that is known from the measured data. When the noise from all the other mechanisms are added as an additional term on the right side (RS) of eq. (2), that equation may look somewhat like the form of a conventional inverse problem.

However, it is in fact different in an important way. The left side (LS) of eq. (2) is a number, not a function, and the equation does not fit into any of the usual inverse problem categories. Even when restricting the class of integrands from power considerations to $L \geq 0$, there probably are still an infinite number of functions, $L = f(\phi,\beta)$, that would satisfy eq. (2).

The problem becomes more tractable if consideration is extended to a small group of n neighboring detectors with contiguous IFOVs that include the one of primary interest. Now eq. (2) takes the expanded form

$$\sum_i E_i\, \delta(\phi - \phi_i, \beta - \beta_i) = \int_{\Omega_n} L(\phi,\beta)\, d\Omega + N \qquad (3)$$

where $\sum$ is a variable summation over the group of n detectors, E_i are the irradiances measured at the i th detector within the group of n, $\delta(x,y)$ is the classical two-dimensional Dirac delta function, ϕ_i and β_i are the coordinates of some point within the i th detector surface, N represents the total additive "noise" and Ω is the total projected solid angle over the IFOV of the group of detectors that is variable. The key is the variability of the range of integration on the RS, and the corresponding summation on the LS of eq. (2). Eq. (3) also does not quite look like a standard integral equation in conventional inverse theories, however it, and the physics of the problem, suggest opportunities to explore that eq. (2) does not. The exploration of some of these appears to be productive.

It is usually assumed without comment that $L(\phi,\beta) = \text{constant} = L_o$ because the IFOV is sufficiently small and whatever is seen in the field of view is uniform. Then

$$E_o = L_o\, \Omega_o \qquad (4)$$

and since Ω_o is a known characteristic of the detector and E_o is measured datum, then L_o is calculated in a trivial manner.

Another aspect of this problem is the question of what coordinates, ϕ_i and β_i, should the measured irradiances, E_i, be associated with. Initially it is simplest to choose the center of each detector's IFOV, but this can be improved with the use of the notion of centroids for those IFOVs, as will be discussed later.

In subpixel spectral demixing one is concerned about determining the identity of objects contained within a single pixel by using the spectral signatures of a class of objects, some of which may be contained within that pixel. Solving this problem does not usually lead to a more accurate data representation, nor an estimate of the spatial variation of radiance within, or in the vicinity of, that pixel (which are the concerns of this paper).

The notion of centroid is used with great accuracy in target detection and tracking, usually for targets seen with the sky as background. Such targets, emanating with sufficiently large peaks in radiance, can be located by some operational optical trackers to an accuracy on the order of one one-hundredth of a pixel or better [7]. In the use of the following centroid, the concern is for the centroid of radiance within each and every pixel of a larger scene, typically when viewing the ground or some extended surface.

III. DERIVATIVE - AS - LIMIT (DAL) ALGORITHMS

Reference [2] approached this problem by first recognizing that a derivative is mathematically defined as a limit. So that eq. (1) can be written as

$$L = dE/d\Omega = \lim_{\Delta\Omega n \to 0} \frac{\Delta E}{\Delta \Omega n} \qquad (5)$$

Then it attempted to approximate the limit by inferring it from the data trend using the data from a sequence of nested sets of nearby neighbors of the detector of interest (as well as the datum from that detector (D_0) as well) that converges to the datum of D_0. Clearly, objects totally contained within the IFOV of a single detector will not be revealed by such an approach.

However calculations are presented in reference [2] for a specific example of synthetic data, for surface features and objects that produce, e.g., a radiance peak (or valley) within D_0 with a half-peak-width (HPW) smaller than the IFOV of D_0 ($IFOV_0$), while continuing to spread at a lower level beyond the borders of $IFOV_0$. These show estimation accuracies greater than normal by the DAL approach. As the HPWs grow larger than $IFOV_0$, the accuracy for smooth curves grows larger. For monotonically increasing or decreasing radiance curves, the accuracy increases as the slope of the curve decreases.

The above statements are true for the calculations performed to date so long as the total noise, N, from other sources, are small enough. Even when applied to aerial imagery of urban areas from altitudes of ten to fifteen thousand feet without corrections for any other error sources, including atmospheric distortion, improvements to imagery were seen. See Figures 1 and 2. However it must be observed that as N grows large, it could be expected that the accuracy of this estimation process will steadily decrease to the point where the results will not be useful. On the other hand, it might also be expected that when other error sources are corrected, such as atmospheric distortion and motion-induced blurring, the improvements may be greater. Refer to Figure 1 for the results of the application of the DAL algorithm to a HYDICE urban scene.

IV. INTERDETECTOR CALIBRATION

The DAL class of algorithms does not directly address the estimation of the spatial variation of radiance in the vicinity or within the IFOV of a detector, from the data trend in a small neighborhood of that detector. One approach to this, as well providing data enhancement, is by using eq. (2) as a consistency relationship applied to an approximation of $L(\phi,\beta)$ obtained from linking the data points between detectors by piecewise-linear interpolation. This approach suffers from the same restriction as the DAL class of algorithms do, in that objects totally contained within a single IFOV will not be represented, but it may be more useful than just the discrete data set $E_i * \delta(\phi - \phi_i, \beta - \beta_i)$, i = 1, 2,..., n.

If one has an approximation to $L(\phi, \beta)$, call it $A_i(\phi,\beta)$, across the IFOV of the i th detector, it may be possible to improve that approximation by requiring that

$$E_i = \iint k_i A_i(\phi, \beta)\, d\Omega \qquad (6)$$

where K_i is a constant whose value is determined from eq. (6). Then an improved approximation to L across that IFOV may be given by

$$B_i(\phi, \beta) = K_i A_i(\phi, \beta) \qquad (7)$$

Sample calculations from synthetic data given next agree with this idea.

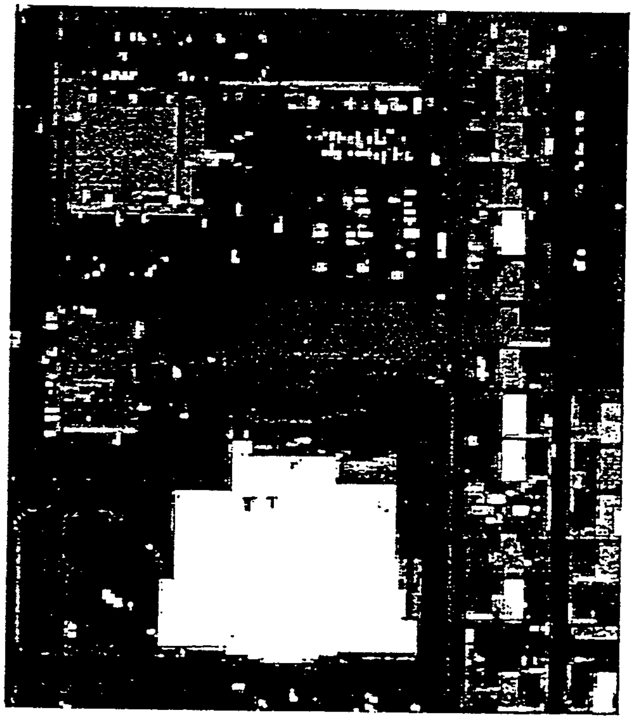

Figure 1.

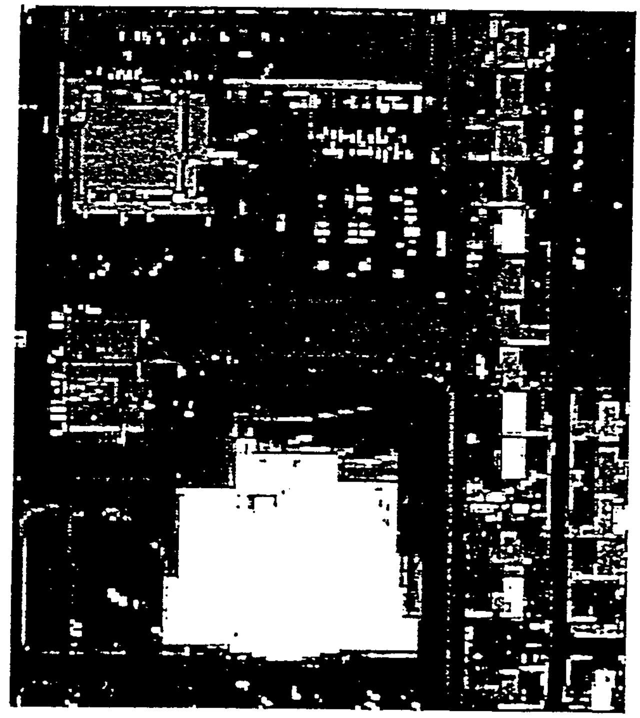

Figure 2.

Figure 1. corresponds to the uncorrected HYDICE image of an urban area. Figure 2 demonstrates the results of the DAL algorithm applied to the HYDICE urban scene.

In order to carry out the above, we obtain the first approximation, A_i, by initially associating the data E_i with the centerpoints of the i th IFOV and later changing the association to the centroids of those IFOVs. In the initial stage we use the approximation from eq. (4) to obtain a radiance from the measured irradiance to associate with the IFOV centerpoint. Then a piecewise-linear approximation is used to connect those discrete points associated with the detectors with contiguous IFOVs in a small immediate neighborhood of the detector of interest.

To demonstrate this initial stage and give numerical results to indicate what is accomplished, we consider a specific example. In order to quantify improvements obtained, a specific spatial variation of radiance will be assumed and the measured irradiance data that a group of ideal detectors would produce (one numerical value per pixel) are calculated. From this synthetic discrete data set we try to infer the original continuous spatial variation of radiance within some of the pixels and compare that with what had been assumed.

For simplicity we consider the following one-dimensional case for the spatial distribution of radiance:

$$L(\phi) = \begin{cases} Lo * \exp(+\phi/a), & \phi < 0 \\ Lo * \exp(-\phi/a), & \phi > 0 \end{cases} \tag{8}$$

where L_O is a constant magnitude, exp(x) represents the exponential function of x and 2a equals the angular width of the IFOV of each of a linear array of identical detectors, with contiguous IFOVs with the center of D_O located at the origin of the local coordinate system. The HPW of this $L(\emptyset)$ is approximately 0.69 (2a), i.e. about 0.7 of the IFOV. Only the data from

the two nearest detectors on each side of D_0 will be used, since when applying the method to real imagery one would usually expect the data in a small neighborhood of a pixel to be "relevant" to the data within the pixel.

To calculate the synthetic irradiance measurement data set, eq. (8) is used in eq. (2) and then eq. (4) is used to transform the results into the set of discrete radiances the assumption of a uniform field would lead to. The resulting radiance "data" set (L, ø) with L normalized to L_0, associated with pixel centerpoints is: (0.0215, -4a), (0.1590, -2a), (0.6321, 0), (0.1590, 2a), (0.0215, 4a). Linear interpolations between these points using the form $L(ø) = m\,ø + b$, m and b are constants, was carried out between the five pixel centerpoints. Then eq. (6) was used to obtain the corrective constants Ki for consistency with the original "measurements." Table 1 illustrates the results of the calculations performed for the center pixel D_0.

Table 1. True and Inferred Normalized (to L_0) Radiances, Based on Centerpoints, for the Center Pixel D_0

Location:	ø = 0	ø = ±a/2	ø = ±a
Actual radiance	1.000	0.606	0.361
Radiance (and error) from	0.632	0.632	0.632
uniformity assumption	(36.8%)	(4.3%)	(75.1%)
Radiance (and error) after	0.951	0.644	0.313
correction with Ki	(4.9%)	(6.2%)	(13.3%)

Note that the results are superior to that from the uniform radiance approximation except near the points where the true radiance function passes near its average value.

V. THE USE OF CENTROIDS

The association of the irradiance data with the centerpoints of the pixels is an arbitrary choice, and arises from its convenience and the lack of information to base choosing other points within the pixel. However once the centerpoints are used, as are done above, in the approximate fashion with sets of linear interpolations for L(ø), it becomes possible to determine more appropriate points through the notion of centroids. Associating the irradiance data with the centroids should lead to an improved approximation to L(ø) when using the linear interpolations between data points.

The context of the traditional use of centroids for optical trackers is described in section II. Here we shall use them within each pixel where we will determine them from the linear interpolations. The definition of centroid as applied to the center pixel is

$$\phi c = \frac{\int_{-a}^{+a} \phi \cdot L(\phi)\,d\phi}{\int_{-a}^{+a} L(\phi)\,d\phi} \qquad (9)$$

Similar usage applies to the other pixels.

When these definitions are used with the linear interpolations for the case given by eq. (8), the results in Table 2 are found for the center pixel D_0, the two pixels adjacent on both sides (D_1) centered at ø = 2a and -2a (which differ only by sign because of symmetry), and the two adjacent to them (D_2) centered on ø = 4a and -4a (which also differ only by sign because of symmetry).

Table 2. True and Inferred Centroids for the Radiance Given by Eq. (8)

Centroid Locations for	Do	D_1	D_2
True Locations	0.000	±1.687(a)	±3.687(a)
Inferred Locations	0.000	±1.747(a)	±3.588(a)
(and errors)	(0%)	(3.6%)	(2.7%)
Centerpoints	0.000	±2.000(a)	±4.000(a)
and errors)	(0%)	(15.7%)	(7.8%)

With approximate values for the centroids now in hand we can recast the data set (L,ø), again using eq. (4) and with L normalized to L_o, as: (0.0215, -3.687a), (0.1590, -1.687a), (0.6321, 0), (0.1590, 1.687a) and (0.0215, 3.687a). These become the basis for a new determination of the linear interpolations between data point locations. Applying eq. (6) to determine a different set of K_i to improve the interpolation approximations, produces the results for the spatial variation of radiance within the pixels shown for D_o in Table 3, and for D_1 in Table 4.

Table 3. True and Inferred Radiances (Normalized to L_o) Using Centroids for the Center Pixel D_o

Location:	ø = 0	ø = ±a/2	ø = ±a
True radiance	1.000	0.607	0.361
Radiance (and error) from	0.632	0.632	0.632
uniformity assumption	(36.8%)	(4.1%)	(75.1%)
Radiance (and error) after	0.921	0.632	0.343
correcting with Ki	(7.9%)	(4.21%)	(2.45%)

Table 4. True and Inferred Radiances (Normalized to Lo) Using Centroids for the Pixels D1 Adjacent to the Center Pixel

Location:	ø = ±a	ø = ±2a	ø = ±3a
True radiance	0.361	0.135	0.050
Radiance (and error) from	0.159	0.159	0.159
uniformity assumption	(56%)	(17.5%)	(218%)
Radiance (and error) after	0.343	0.133	0.062
correcting with Ki	(2.5%)	(1.7%)	(24.7%)

It is clear from Tables 3 and 4 that the procedure described using centroids gives a better description of the spatial variation of radiance within the pixels than does the assumption of uniformity for the case considered. Furthermore, the comparison of Tables 1 with 3 indicates that the use of centroids as data points gives somewhat better results than does the use centerpoints. When what is desired from this information is a single value of radiance for a pixel, the choice of value from the continuum calculated depends on the objectives. For example, when peak values occur within a pixel, the value of the peak within that pixel may be most useful in some circumstances.

VI. CONCLUSIONS

An apparently new type of inverse problem has been considered in which the spatial variation of radiance within individual pixels is to be reconstructed from the discrete set of irradiances, one digital number per pixel, measured by an array of detectors with contiguous IFOVs. Two classes of algorithms have been discussed. The first, DAL, does not retrieve detailed spatial profiles of radiance, but considers a sequence of nested sets of neighboring detectors, the data from which is used to estimate the limit that defines the derivative in the radiance/irradiance relationship $L = dE/d\Omega$ [2]. The second class of algorithms, called interdetector calibration, does estimate the intrapixel spatial variation of radiance using the data trends from the neighboring pixels and the datum of the pixel of interest.

In the past, it has customarily been assumed, usually without discussion, that the radiance is simply a constant within the pixel. This yields the radiance for a pixel from $E = \int L \, d\Omega$, the measured irradiance (a single digital number) and the designed Ωo in an elementary manner. However when there is a concern for relatively small objects, rapidly varying surface conditions or topography, such an assumption of uniformity may be counterproductive. Airborne imagery illustrating the enhancement using a DAL algorithm and calculations of the accuracy of the spatial variations of intrapixel radiance supplied by two interdetector calibration algorithms has been presented.

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